IMPROVED DECONVOLUTION FOR LOW SIGNAL-TO-NOISE RATIO SEISMIC DATA

Abolfazl M. Amini, George E. Ioup, Juliette W. Ioup, and Reginald Powe
Department of Physics and Geophysical Research Laboratory
University of New Orleans, New Orleans, LA 70148

key words: seismic data processing, deconvolution, iterative deconvolution, iterative noise removal, noise simulations

ABSTRACT

The always-convergent iterative method (AC) of Ioup and the reblurring/mirror image iterative procedure (RB) of Kawata and Ichioka and LaCoste are compared to the least squares technique (LS) for low signal-to-noise ratio (SNR) seismic data. To study the resolution as well as the mean squared error (MSE), a spike train with systematically varying separations is employed. After it is convolved with a wavelet, noisy test cases are generated for SNR's from 1.1 to 14.8 and all three deconvolution methods are applied. The MSE for each case is calculated. Then the average MSE is obtained and its dependence on SNR is given. The AC and RB give lower MSE than the LS. Sample results are shown for the noisy data, the AC noise removal, and all three deconvolution techniques. The optimum iteration number is plotted versus SNR for RB, AC noise removal, AC deconvolution, and the sum of the last two.

INTRODUCTION

It is well established that deconvolution, especially spiking deconvolution, can amplify noise. See, for example, the discussion given by Ioup and Ioup (1983). Therefore seismic data of low signal-to-noise ratio (SNR) are difficult to deconvolve. Two iterative techniques of deconvolution, the always-convergent iterative technique (AC) of Ioup (1981), and the reblurring/mirror image iterative procedure (RB) of Kawata and Ichioka (1980) and LaCoste (1982), are less sensitive to noise amplification than the standard least squares approach (LS) (Robinson, 1980; Robinson and Treitel, 1980). In order to show this explicitly and examine the performance of all three deconvolution techniques for noisy data, we construct a very difficult test after Powe et al. (1985). We also follow the optimization methodology of Amini et al. (1986). To test the performance of the three techniques, an examination is made of the mean squared error (MSE) after deconvolution as a function of the SNR. Many data sets are averaged at each SNR to obtain these results. Since the MSE does not give a complete picture of the relative performance, individual data sets are also examined after deconvolution by the three approaches. Some details of the use of the iterative techniques are also discussed.

METHODOLOGY

To use the iterative techniques for spiking deconvolution, the wavelet must first be extracted. For our model, we assume that this has already been done and we use the minimum phase wavelet shown in Figure 1(a). Since the wavelet is minimum phase, the application of the LS method is straightforward. To examine the limits of resolution, a variable separation spike train, shown in Figure 1(b), is adopted. Because the wavelet is 46 samples long and the separations of the spikes vary from two sample intervals up to seven sample intervals, this is a severe test. The difficulty of resolving the individual spikes may be seen from the resulting seismic trace, shown in Figure 1(c).

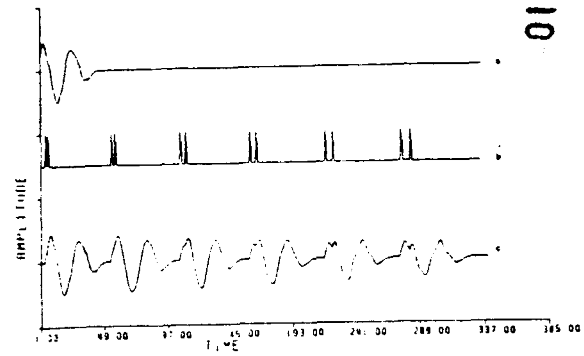

Fig. 1. (a) Wavelet, (b) Spike Train, (c) Convolution of (a) and (b).

In order to apply the iterative approaches and accomplish the comparison of the techniques, we use the statistical simulation methodology developed by Wright (1980), Wright and Ioup (1981), Ioup and Ioup (1981), Leclere (1984), Leclere et al. (1985), and Amini et al. (1986). Noise is added to the data based on a scale factor which produces noise sets having a SNR approximately equal to the one of interest. Recognizing the very large variability possible in the spectral characteristics of the noise from one noise set to another, we have chosen to work with time-domain generated noise whose statistics are specified by a given density function, in this case, a Gaussian. This is a not a limitation. Any density function could be chosen. The low SNR's used in this study range from three to 40. The SNR definition used here is the peak signal value divided by the standard deviation of the noise. Alternately, a common definition is the standard deviation of the signal divided by the standard deviation of the noise. For our data the SNR by the latter definition is 1/2.7 times the former, so the SNR range is then 1.1 to 14.8. Twenty to fifty noisy test cases at each SNR sample point are generated for statistical reliability. We then give the average results for each deconvolution method.

The reblurring iterations are applied as a single set of iterations. The number of iterations required is generally large. The always-convergent iterations are in two parts, a noise removal iteration followed by a deconvolution iteration. Optimizations for these iterations for seismic data have been given by Amini et al. (1986).

The LS filter length is 999, long enough so that the deconvolution is not degraded by having too short a filter.

RESULTS

In Figures 2(a) and (c) we show a noisy data sample for two intermediate SNR's, 10 (3.7) and 30 (11), respectively. Figure 2(b) is the result of applying the AC noise removal iterations to the data of Figure 2(a), while Figure 2(d) is the corresponding result for Figure 2(c). The smoothing effect is apparent.

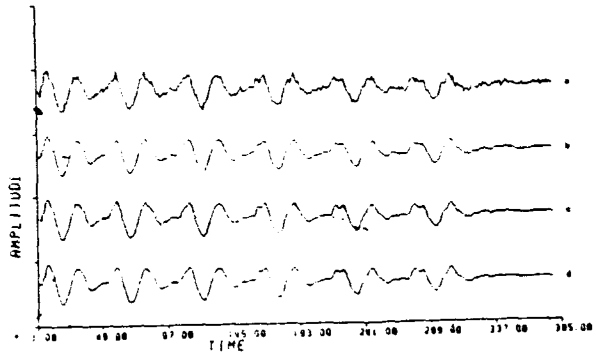

Fig. 2. (a) SNR 10 data, (b) AC smoothed (a), (c) SNR 30 data, (d) AC smoothed (c).

Figure 3 shows a deconvolution result for a SNR of 30 (11) for all three methods. In Figure 3(a) the AC result is given, while the RB is in Figure 3(b) and the LS is in Figure 3(c). While the resolution of the LS technique is comparable to or slightly better than the iterative techniques, the LS deconvolved data are affected by noise to a significantly larger extent. The noise level as a percentage of peak height is greater. This is reflected in the calculated MSE to be discussed subsequently. There are only slight differences between the two iterative results.

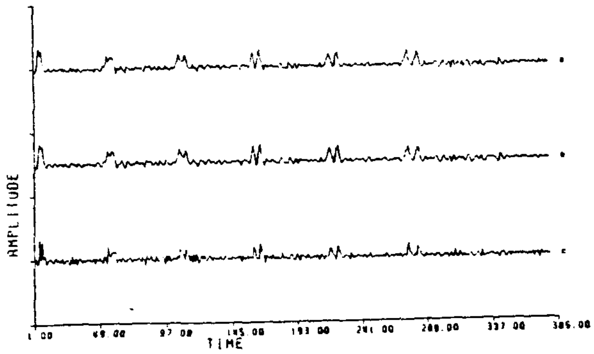

Fig. 3. SNR 30 data deconvolution (a) AC, (b) RB, (c) LS.

A test case with SNR ~ 10 (3.7) is deconvolved to give the results shown in Figure 4. The AC, RB, and LS deconvolutions are in Figures 4(a), (b), and (c), respectively. Again the resolution of the LS method is good, but the noise is so large that it is difficult to distinguish the true peaks from false ones due to noise. The resolution of the iterative techniques is decreased due to the increased noise level, but all peaks, whether resolved or not, rise above the noise. The standard trade-off in deconvoluion is resolution versus noise amplification. For the iterative techniques the optimum iteration number has been selected to minimize the MSE. Any measure could have been used. In particular, one which gives more resolution and more noise amplification may be desirable in some circumstances (Andrews and Hunt, 1977; Hunt, 1978).

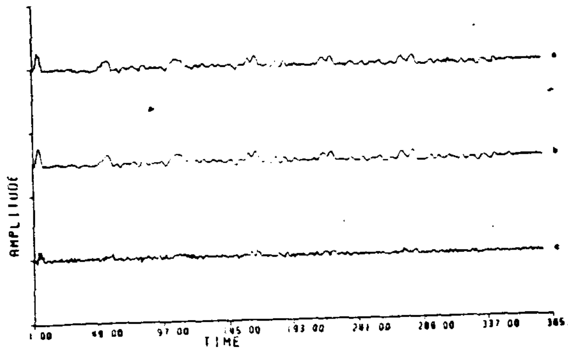

Fig. 4. SNR 10 data deconvolution (a) AC, (b) RB, (c) LS.

Figure 5 presents the average MSE after deconvolution versus the SNR. The lower curves give the MSE for the iterative techniques, while the upper curve shows the LS MSE. The larger MSE for the LS corresponds to the larger noise relative to the signal in the LS deconvolved data.

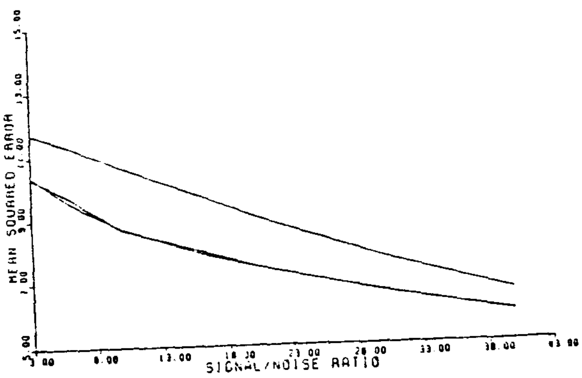

Fig. 5. MSE after devonvolution; upper curve, LS; lower curves, AC and RB.

In Figure 6 the average numbers of iterations used at each SNR are summarized. Although the iterative techniques are now available as equivalent filters for rapid application to seismic data, this study was done with the standard iterative approach. Investigations using the latter are important for the correct application of the equivalent filters. Since the RB iteration numbers are large compared to the AC, they are divided by ten to give Figure 6(a). The average AC noise removal iteration numbers are shown in Figure 6(b). In Figure 6(c) the average numbers of deconvolution iterations for the AC are shown. Finally, Figure 6(d) gives the sum of the AC noise removal and deconvolution iterations, to show the total needed. The AC uses fewer iterations than the RB, except at the lowest SNR. These numbers come from optimizing all the noisy test cases at a given SNR and taking the average of the results.

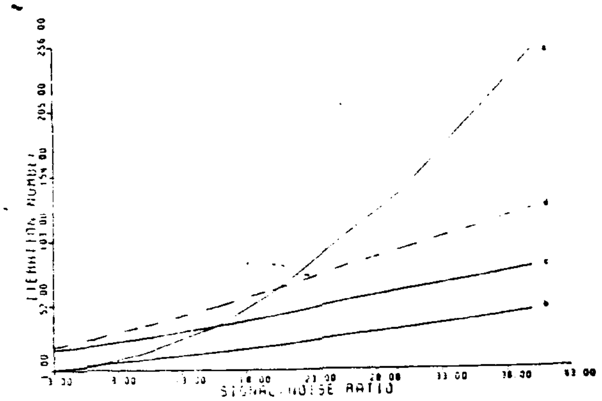

Fig. 6. Optimum average iteration number (a) RB number/10, (b) AC noise removal, (c) AC deconvolution, (d) AC noise removal and AC deconvolution.

CONCLUSION

When the wavelet has been determined, iterative deconvolution techniques are a valuable alternative to LS for the deconvolution of seismic data. They offer control over noise amplification and they can be applied quickly (as single equivalent filters).

REFERENCES

Amini, A. M., Ioup, G. E., Ioup, J. W., and Powe, R., 1986, Optimization of convergent iterative deconvolution for seismic data: EOS Trans. Amer. Geophys. Union, 67, 1088.

Andrews, H. C. and Hunt, B. R., 1977, Digital image restoration: New Jersey, Prentice-Hall.

Hunt, B. R., 1978, Digital image processing, in Applications of digital signal processing: A. V. Oppenheim, Ed., New Jersey, Prentice-Hall, p. 169-237.

Ioup, G. E., 1981, Always-convergent iterative noise removal and deconvolution: Bull. Am. Phys. Soc., v. 26, p. 1213.

Ioup, G. E., and Ioup, J. W., 1981, Optimum use of Morrison's iterative noise removal method prior to linear deconvolution, Bull. Am. Phys. Soc. v. 26, p. 1213.

Ioup, G. E., and Ioup, J. W., 1983, Iterative deconvolution: Geophysics, v. 48, p. 1287-1290.

Kawata, S., and Ichioka, Y., 1980, Iterative image restoration for linearly degraded images. I. Basis: J. Opt. Soc. Am., v. 70, p. 762-768;II. Reblurring procedure: J. Opt. Soc. Am., v. 70, p. 768-772.

LaCoste, L. J. B., 1982, Deconvolution by successive approximations: Geophysics, v. 47, p. 1724-1730.

Leclere, J. H., 1984, Optimum use of Morrison's iterative method of noise removal for deconvolution: M.S. thesis, University of New Orleans.

Leclere, J. H., Ioup, George E., and Ioup, Juliette W., 1985, A statistical optimization study of iterative noise removal for deconvolution: EOS Trans. Amer. Geophys. Union v. 66, p. 983.

Powe, Reginald, 1985, A comparison of convergent iterative deconvolution methods with the least squares technique for synthetic seismic data: M. S. thesis, University of New Orleans.

Powe, Reginald, Ioup, George E., and Ioup, Juliette W., 1985, A comparison of convergent iterative deconvolution methods with the least squares technique for synthetic seismic data, Expanded Abstracts of the Society of Exploration Geophysicists Fifty-Fifth Annual International Meeting and Exposition, p. 556-558; Geophysics v. 51, p. 497.

Robinson, E. A., 1980, Physical applications of stationary time-series: New York, Macmillan.

Robinson, E. A., and Treitel, S., 1980, Geophysical signal analysis: New Jersey, Prentice-Hall.

Wright, K. A. R., 1980, A study of Morrison's iterative noise removal method: M. S. thesis, University of New Orleans.

Wright, K. A. R., and Ioup, G. E., 1981, Optimum use of Morrison's iterative noise removal method for noise minimization: Bull. Am. Phys. Soc. v. 26, p. 1213.